

Article

Spatially Heterogeneous Effects of Microscale Built Environments on PM_{2.5} Concentrations Based on Street View Imagery and Machine Learning

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Abstract

PM_{2.5} pollution is a significant environmental problem in global urbanization. However, traditional macro-scale studies are constrained by data resolution limitations, failing to accurately characterize the microscale built environment or thoroughly investigate its spatially heterogeneous effects on PM_{2.5} concentrations. To address this gap, this study constructs a multidisciplinary framework of “Street View Imagery element extraction–spatial heterogeneity modeling–planning strategy optimization” with Xi'an as the case. Leveraging machine learning techniques, the study employs the ResNet50 deep learning model and the ADE20K dataset to precisely extract ten microscale built environment factors from tens of thousands of street view images. Combined with the High-resolution and High-quality Ground-level PM_{2.5} Dataset for China, Ordinary Least Squares (OLS), Geographically Weighted Regression (GWR), and Multiscale Geographically Weighted Regression (MGWR) models were used to systematically reveal the impacts of the microscale built environment on PM_{2.5} concentrations. Ten built environment factors were identified with varying spatial heterogeneity in their effects on the PM_{2.5} concentrations, as follows: (1) factors with positive effects, in descending order of strength, include building, wall, fence, tree, sky, and grass; (2) factors with negative effects, in descending order of strength, include sidewalk, plant, and car; (3) compared with other factors, the road factor showed a relatively weaker effect. This research provides decision-making support for targeted urban planning and environmental protection, while offering valuable references for air pollution control in other cities.

Keywords: street view imagery; built environment; PM_{2.5}; MGWR; spatial heterogeneity

Academic Editor: Theodosiou Theodoros

Received: 26 August 2025

Revised: 9 October 2025

Accepted: 11 October 2025

Published: 16 October 2025

Citation: Hu, T.; Wu, K.; Wu, Y.; Wang, L. Spatially Heterogeneous Effects of Microscale Built Environments on PM_{2.5} Concentrations Based on Street View Imagery and Machine Learning. *Buildings* **2025**, *15*, 3721. <https://doi.org/10.3390/buildings15203721>

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1. Introduction

Air pollution is a major global public health issue. PM_{2.5} (particulate matter with an aerodynamic diameter of 2.5 µm or less) is one of the primary air pollutants and a key indicator of air quality, posing a serious threat to public health [1,2]. When inhaled, PM_{2.5} particles can penetrate deep into the lungs and even enter the bloodstream, leading to numerous health complications. Studies have shown that exposure to PM_{2.5} can result in a range of diseases, including respiratory diseases [3,4], cardiovascular diseases [5,6], cancer [7–9], pulmonary diseases [10,11], neurological disorders [12,13], and even an increased risk of premature death [14–16]. Worldwide, PM_{2.5} is responsible for millions of

deaths [17–19]. Therefore, the issue of global PM_{2.5} pollution remains critical, and urgent and effective measures are required to address it.

Air pollution has become one of the most severe environmental issues in China [20]. In recent years, the Chinese government has implemented a series of policies to mitigate PM_{2.5} pollution [21–24]. The State Council of the People's Republic of China issued the Clean Air Action Plans in 2013, 2018, and 2023, including the Air Pollution Prevention and Control Action Plan, the Three-Year Action Plan for Winning the Blue Sky Defense Battle, and the Action Plan for Continuous Improvement of Air Quality. These policies aim to significantly reduce the total emissions of major air pollutants, coordinate reductions in greenhouse gas emissions, and further decrease PM_{2.5} concentrations [25–27]. Although these Clean Air Action Plans have yielded marked improvements in reducing PM_{2.5} pollution levels and enhancing air quality since 2013 [21,28–30], China's annual average PM_{2.5} concentration still exceeds the World Health Organization's current annual guideline value of 5 µg/m³ [31]. Consequently, PM_{2.5} pollution continues to pose a serious challenge for China.

The urban built environment refers to the human-made surroundings that support human activities, including buildings, roads, and other infrastructure [32]. Exploring the effect of the built environment on PM_{2.5} concentrations and identifying effective strategies to reduce PM_{2.5} pollution have long been central concerns in the fields of urban planning, city management, environmental protection, and public health. Numerous domestic and international studies have revealed a complex relationship between various elements of the urban built environment and PM_{2.5} concentrations. These elements include urban landscape patterns [33], urban morphology [34–36], and land use [37], all of which significantly affect PM_{2.5} concentrations. Although substantial research has been conducted on how the built environment affects PM_{2.5} concentrations, most studies have relied on two-dimensional data to quantify the urban built environment. For example, most remote sensing imagery is based on a top-down perspective and focuses on large-scale monitoring data, making it unsuitable for detailed analysis of the microscale built environment. Zhou et al. employed mobile monitoring combined with two-dimensional built environment indicators, revealing the spatiotemporal heterogeneity of road-level PM_{2.5} and its relationship with the microscale built environment [38]. However, at present, research on the spatially heterogeneous effects of the microscale built environment on PM_{2.5} concentrations from a three-dimensional perspective remains limited. Therefore, selecting appropriate data sources and research methods is essential for thoroughly investigating the relationship between microscale built environments and PM_{2.5} concentrations.

In recent years, with the advancement of computer vision and machine learning technologies, Street View Imagery has emerged as a novel data source, providing new opportunities for urban research and planning [39–41]. With advantages such as high resolution, easy accessibility, and broad spatial coverage, Street View Imagery has been widely used in studies on the green view index [42–44], urban vitality [45,46], spatial perception [47], land surface temperature [48,49], urban color [50–52], urban economy [53], carbon emissions [54], urban visual environments [55], housing prices [56,57], and air pollution [58–60]. Qi et al. revealed that Street View Imagery has significant potential for predicting street-level air pollution [61]. Furthermore, over the past decade, Street View Imagery has been extensively employed to analyze urban street characteristics and the built environment [62]. Therefore, this study employs Street View Imagery as a distinctive data source to examine the relationship between micro-scale urban built environments and PM_{2.5} concentrations.

As a representative high-density city in China and a heavily polluted city in the Fenwei Plain, Xi'an is frequently affected by air pollution due to its complex urban built environment. Accordingly, this study integrates knowledge from urban planning, environmental

science, and computer science to establish a multidisciplinary framework for studying $PM_{2.5}$ concentrations. By combining Street View Imagery, machine learning techniques, and spatial regression models, the research aims to help urban planners and administrators gain more targeted insights into the built environment factors affecting air pollution in Xi'an. This study seeks to address the following questions:

- (1) What is the effect of the micro-scale urban built environment on $PM_{2.5}$ concentrations?
- (2) Can the Multiscale Geographically Weighted Regression (MGWR) model accurately explain the effect of the microscale built environment on $PM_{2.5}$ concentrations?
- (3) What is the strength of the effect of microscale built environment factors on $PM_{2.5}$ concentrations?

2. Methods

2.1. Research Framework

The research framework, as illustrated in Figure 1, can be divided into the following stages:

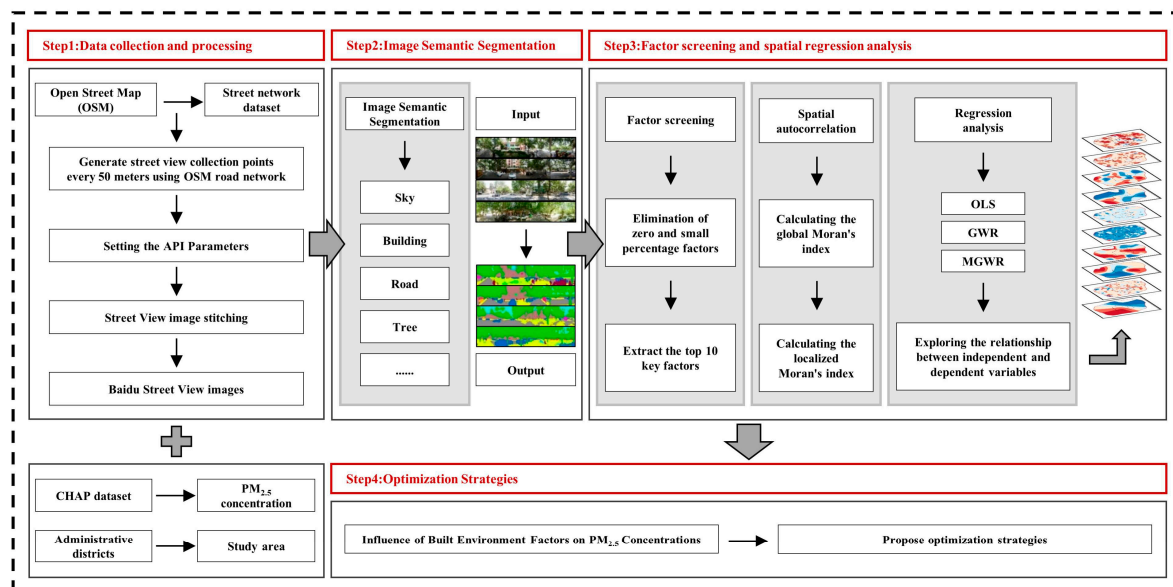


Figure 1. Research framework.

(1) Acquire OSM road network data, generate Street View collection points every 50 m along the OSM road network, set API parameters to collect Baidu Street View Imagery data, and stitch the images. Obtain $PM_{2.5}$ concentration data and administrative division data to ensure data accuracy and completeness.

(2) Employ the ResNet50 deep convolutional neural network architecture combined with the ADE20K dataset to perform semantic segmentation on Street View Imagery, quantifying various elements within the images.

(3) Screen key factors with effects on $PM_{2.5}$ concentrations. Utilize spatial autocorrelation methods to calculate global Moran's I and local Moran's I, exploring the aggregation and distribution patterns of $PM_{2.5}$ concentrations at both regional and local scales within the study area.

(4) Compare the Ordinary Least Squares (OLS), Geographically Weighted Regression (GWR), and Multi-Scale Geographically Weighted Regression (MGWR) models to select the optimal model for comprehensively explaining the spatially heterogeneous effects of urban built environments on $PM_{2.5}$ concentrations.

(5) Summarize the spatial heterogeneity characteristics between urban built environments and PM_{2.5} concentrations in Xi'an, providing optimization strategies for urban planning and environmental protection in the study area.

2.2. Study Area

Xi'an, located in the central part of the Guanzhong Plain, is bounded by the Qinling Mountains to the south, the Wei River to the north, and embraced by the Lishan Mountains on its eastern periphery. Its geographical coordinates span from 107°40' E to 109°49' E and from 33°42' N to 34°45' N. The city has a warm-temperate semi-humid continental monsoon climate, characterized by distinct seasons with an annual average temperature ranging from 13.5 °C to 14.9 °C. By the end of 2023, Xi'an administered 11 districts and 2 counties, covering a total area of 10,096.89 km² and supporting a permanent population of 13.0782 million. Xi'an, serving as an international comprehensive transportation hub city, a critical node city of the Belt and Road Initiative, a national central city of China, a major industrial city in Northwest China, and the core city of the Guanzhong Plain urban agglomeration, occupies a pivotal strategic position. However, as the provincial capital of Shaanxi and situated within the Fenwei Plain (a heavily polluted region), Xi'an faces severe PM_{2.5} pollution challenges.

The study area is the central urban area enclosed by the Xi'an Ring Expressway, a region characterized by complex built environments, diverse urban morphologies, high population density, intense traffic flow, mixed land use, and pronounced street canyon effects. The area also features a distinctive checkerboard-radial road network. Furthermore, comprehensive coverage of Baidu Street View Imagery data in this region enhances the accuracy and reliability of research outcomes. Figure 2 shows the overview map of the study area. This research selects the PM_{2.5} pollution problem of Xi'an, a typical polluted city in the Fenwei Plain, for the study, which has significant representativeness and urgency.

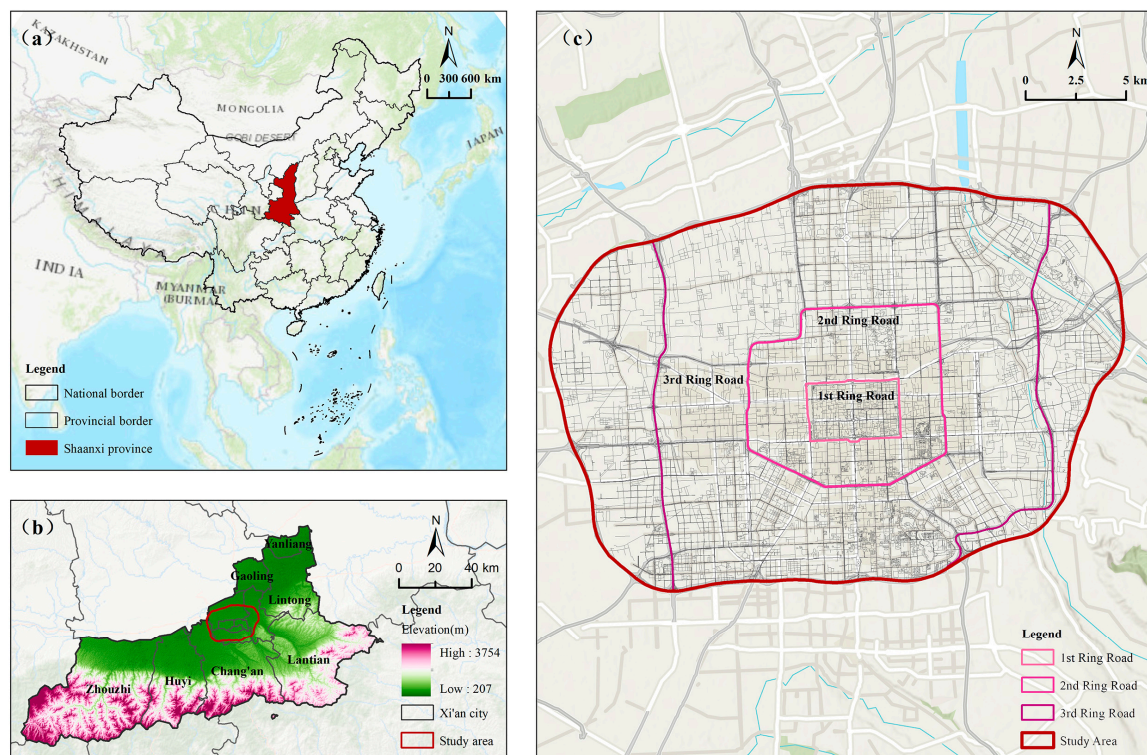


Figure 2. Overview of the study area: (a) location of Shaanxi Province within China; (b) location of the study area within Xi'an City; (c) boundary of the study area. Note: Administrative boundary vector data are sourced from the National Geomatics Center of China (Approval No. GS (2024) 0650).

2.3. Street View Imagery Data Collection

Street View Imagery, as a data source capable of visually reflecting built environment characteristics, has been widely applied in urban planning, environmental protection, and other fields. Google Street View (GSV), a globally renowned map service, provides extensive coverage in over 90 countries and regions. However, due to policy restrictions, Google services are unavailable in mainland China, and GSV has almost no coverage in this region. Tencent Street View (TSV) has covered most cities in mainland China since 2011, but its data updates have been discontinued due to business adjustments [63]. In contrast, Baidu Street View (BSV) covers 652 cities in mainland China, with a total road imagery length of 2.295 million kilometers, covering more than 80% of Chinese cities. Its data quality is comparable to GSV, and it has been widely utilized in various research fields [39].

This study selected Baidu Maps (<https://map.baidu.com>) as the data source for Street View Imagery, focusing on the area within the Xi'an Ring Expressway. The specific data collection process is as follows: Firstly, road network data of the study area were downloaded from OpenStreetMap (<https://www.openstreetmap.org/>). Using ArcGIS 10.8 software, Street View Imagery sampling points were set at 50 m intervals along the road network, with a total of 45,404 sampling points established in the study area. Secondly, Python 3.9 software was utilized to invoke Baidu Maps' API, with camera angle parameters set to 0°, 90°, 180°, and 270° to collect Street View Imagery from the front, back, left, and right directions for each sampling point. The images had a resolution of 600 × 480 pixels, and the vertical viewing angle was set to 7°. After data collection, data cleaning and removal of invalid data were performed, resulting in 133,860 valid Street View Imagery. Finally, the front, back, left, and right images of each sampling point were stitched to generate 33,465 panoramic Street View Images for subsequent analysis. Table 1 presents the parameter settings for Baidu Maps' panoramic static images.

Table 1. Baidu map panoramic static imagery parameter settings.

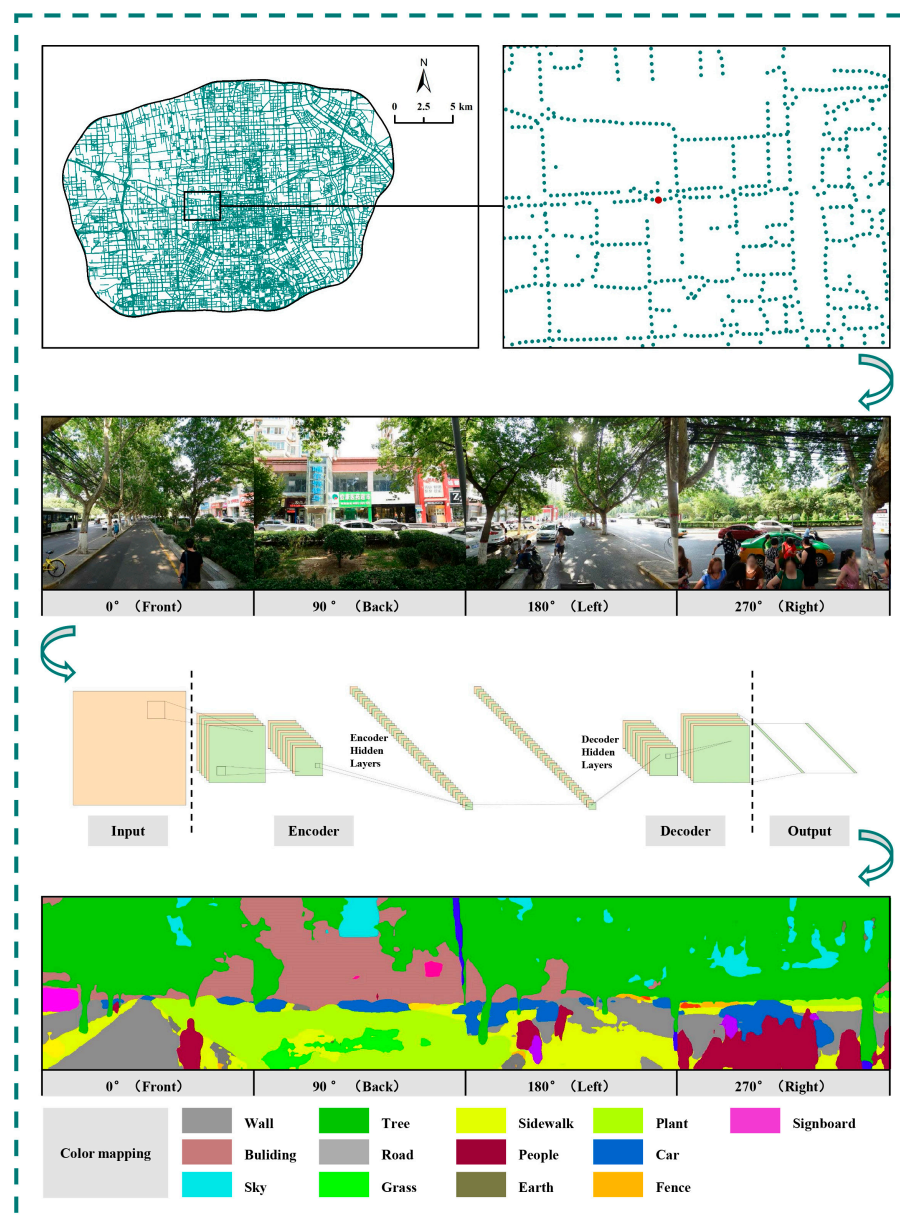
Parameter	Description	Default	Set Value
Heading	Horizontal visual angle of imagery, range [0, 360]	0	0/90/180/270
Pitch	Vertical visual angle of imagery, range [0, 90]	0	7

2.4. Semantic Segmentation Model and Dataset

ADE20K is the largest open-source dataset for semantic segmentation and scene parsing released by the MIT computer vision team. The dataset includes 150 categories of elements, such as sky, road, car, and plant, and has been widely used for semantic segmentation of Street View Imagery [64]. ADE20K comprises three types of data: training data (20,210 images), validation data (2000 images), and test data (3000 images) [65]. ResNet50 is a commonly used convolutional neural network architecture widely applied in image recognition tasks. The model architecture consists of an encoder and a decoder. The CSAILVision framework, released on GitHub (<https://github.com/CSAILVision/semantic-segmentation-pytorch>, accessed on 30 September 2025) by the MIT Computer Science and Artificial Intelligence Laboratory (CSAIL), was adopted in this study. This project is a mature PyTorch framework based on the ResNet50 model pre-trained on the ADE20K dataset, which has been extensively cited and applied in the computer vision community. This ensures the reproducibility and reliability of the approach. As shown in Table 2, the performance of the ResNet50 model indicates its effectiveness in segmenting Street View Imagery. Figure 3 illustrates the process of Street View Imagery collection and semantic segmentation.

Table 2. ResNet50 model performance metrics in street view imagery processing.

Architecture	Multiscale Testing	Mean IoU	Pixel Accuracy (%)	Overall Score	Inference Speed (fps)
ResNet50dilated	NO	41.26	79.73	60.50	8.3
+ PPM_deepsup	Yes	42.14	80.13	61.14	2.6

**Figure 3.** Street view imagery collection and image semantic segmentation process.

2.5. $PM_{2.5}$ Concentration Data

This study selected the High-resolution and High-quality Ground-level $PM_{2.5}$ Dataset for China [66,67], provided by the National Tibetan Plateau Data Center (<http://data.tpdc.ac.cn>). This dataset offers $PM_{2.5}$ data from 2000 to the present, with a ten-fold cross-validation coefficient of determination (R^2) of 0.92 and a root mean square error (RMSE) of $10.76 \mu\text{g}/\text{m}^3$. Covering the entire territory of China, the dataset has a spatial resolution of 1 km and temporal resolutions of daily, monthly, and annual scales, with units expressed in $\mu\text{g}/\text{m}^3$.

Compared to traditional ground-based monitoring station data, the ChinaHighAirPollutants (CHAP) dataset offers advantages such as extensive coverage, a long time series, high spatial resolution, and low cost. In recent years, it has been widely applied in multiple fields, including air pollution research [68–70], environmental science [6,71–73], and medical research [74–76]. Furthermore, the validity and accuracy of this dataset have been extensively studied and verified.

According to data released by the Ministry of Ecology and Environment of the People's Republic of China in 2023, Xi'an ranked as the fifth-lowest among 168 key cities in China in terms of air quality [77]. Therefore, the 2023 annual average PM_{2.5} pollution data were selected for analysis in this study. The selection of this specific timeframe aims to better elucidate the spatial heterogeneity effects of Xi'an's microscale built environment on PM_{2.5} concentrations, thereby providing a scientific basis for improving air quality in Xi'an.

2.6. Spatial Autocorrelation Analysis

Spatial autocorrelation analysis is commonly employed in research fields such as environmental science, urban planning, and ecology [78–81]. This study calculated the Global Moran's I to analyze the spatial clustering and dispersion patterns of PM_{2.5} concentrations within the study area. The value of Global Moran's I ranges from -1 to 1 , where values greater than 0 indicate spatial positive autocorrelation, values less than 0 indicate spatial negative autocorrelation, and values close to 0 suggest random spatial distribution. The calculation formula for Global Moran's I is as follows:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (x_j - \bar{x})^2} \quad (1)$$

In the formula, I represents the Global Moran's I ; x_i and x_j denote the PM_{2.5} concentrations in grids i and j , respectively; $\bar{x}$ signifies the mean PM_{2.5} concentration; W_{ij} denotes the spatial weight matrix; and n represents the total number of samples.

Building on the previous analysis, this study further calculated the Local Moran's I to examine the spatial clustering of high and low PM_{2.5} concentrations within the study area. The Local Moran's I values can be categorized into four types of clusters: the high–high cluster, high–low cluster, low–low cluster, and low–high cluster. The calculation formula for Local Moran's I is as follows:

$$I_i = \frac{(x_i - \bar{x}) \sum_{j=1, j \neq i}^n W_{ij} (x_j - \bar{x})}{S_i^2} \quad (2)$$

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^n (x_j - \bar{x})^2}{n - 1} - (\bar{x})^2 \quad (3)$$

In the formula, I_i denotes the Local Moran's I , S_i^2 represents the variance of PM_{2.5} concentrations, and the definitions of other variables remain consistent with those in Equation (2).

2.7. Spatial Regression Analysis

In urban planning, environmental science, and related research fields, fishnet grids are commonly employed for spatial partitioning to facilitate data integration and overlay analysis [59,82]. Consequently, this study utilized ArcGIS 10.8 software to generate a fishnet tool, dividing the study area into 200 m × 200 m grids. Ten urban built environment factor

datasets were then assigned to the corresponding grids. During spatial analysis, these fishnet grids served as the fundamental spatial unit, laying the groundwork for subsequent spatial regression analysis.

To analyze the effects of microscale built environment factors on PM_{2.5} concentrations, three spatial regression models were used in this study. First, the OLS model was used to establish the base regression model. Second, the GWR model was used to explain the spatial non-stationarity. Finally, the MGWR model was used to explain the spatial heterogeneity of the effect factors.

(1) OLS Regression Model

The OLS regression model has been widely adopted in urban planning, environmental science, and related fields [83,84]. As a foundational global linear regression model, it does not account for spatial variations. In this study, the OLS model was initially employed to examine whether significant linear relationships exist between built environment factors and PM_{2.5} concentrations. The OLS model is formulated as:

$$Y = X\beta + \epsilon \quad (4)$$

In the formula, Y represents the dependent variable, X denotes the matrix of explanatory variables, β signifies the coefficient vector, and ϵ is the random error term vector.

(2) GWR Regression Model

Due to the limitation of the OLS regression model in neglecting spatial heterogeneity, the GWR model is a modification of the OLS model. The GWR model permits regression coefficients to vary spatially by employing a uniform bandwidth, thereby capturing spatial non-stationarity. The GWR model is formulated as:

$$Y_i = \alpha_{0(u_i, v_i)} + \sum_{k=1}^m a_{k(u_i, v_i)} X_{k(u_i, v_i)} + \epsilon_i \quad (5)$$

In the formula, Y_i represents the PM_{2.5} concentration, (u_i, v_i) denotes the coordinates of the i -th sampling point, $\alpha_0(u_i, v_i)$ is the model intercept, α_k signifies the regression coefficient of the k -th independent variable at (u_i, v_i) , $X_k(u_i, v_i)$ is the k -th attribute at location i , and ϵ_i is the random error term.

(3) MGWR Regression Model

The MGWR model is a modification of the GWR model. By assigning distinct bandwidths to each explanatory variable, it effectively addresses spatial non-stationarity and comprehensively reveals spatial heterogeneity across various effect factors. Research has demonstrated the MGWR model's notable advantages in fields like atmospheric pollution. For example, Duan et al. utilized the MGWR model to elucidate the spatial heterogeneity between three-dimensional urban landscape patterns and PM_{2.5} pollution in Wuhan [68]. Wu et al. employed the MGWR model to analyze multi-scale interactions and spatial heterogeneity of natural and socioeconomic factors affecting PM_{2.5} concentrations [85]. Zhou et al., focusing on the Niger River Basin in West Africa, applied the MGWR model to investigate relationships between PM_{2.5} concentrations and natural/land-use factors [86]. These studies fully validate the effectiveness of the MGWR model in revealing spatial heterogeneity from different perspectives and regions. Therefore, the present study employs the MGWR 2.2 software, incorporating built environment factors as independent variables and PM_{2.5} concentrations as the dependent variable, to explore their spatial heterogeneity. The MGWR model is formulated as:

$$Y_i = \alpha_{0(u_i, v_i)} + \sum_{k=1}^m a_{bwk(u_i, v_i)} X_{k(u_i, v_i)} + \epsilon_i \quad (6)$$

The MGWR model is a modification of the GWR model. In the formula, Y_i represents the $PM_{2.5}$ concentration at the i -th sampling point, (u_i, v_i) denotes the coordinates of the i -th sampling point, m is the total number of sampling points, a_{bwk} is the k -th explanatory variable with an added bandwidth parameter bw , and each explanatory variable has a distinct spatial scale. ε_i is the random error term.

3. Results

3.1. Screening of Urban Built Environment Factors

This study employs the ResNet50 deep convolutional neural network architecture combined with the ADE20K dataset to perform semantic segmentation on 33,465 panoramic Street View Images of the study area, quantifying various elements within the images. The semantic segmentation results enable the calculation of the percentage of each element relative to the total elements in the Street View Imagery. The ADE20K dataset encompasses diverse scene elements, including 150 semantic categories covering indoor and outdoor elements such as architecture, natural landscapes, transportation facilities, and furniture [64,65]. Given that not every element can be considered an urban built environment factor affecting $PM_{2.5}$ concentrations, it is necessary to screen the elements in the semantic segmentation results of Street View Imagery.

This study adopts a three-stage approach to screen indicator factors, ensuring efficient and accurate identification of key factors. First, during the preliminary filtering stage, factors with zero or low proportions (such as Ship, Fan) were excluded from the 150 elements derived from Street View Imagery semantic segmentation results, resulting in the elimination of 125 invalid variables. Second, in the primary factor identification stage, elements were ranked in descending order based on their average proportions in Street View Imagery, and the top 10 key built environment factors with the highest proportions were extracted, including sky, building, road, tree, and car. Relevant studies also indicate that factors such as sky, building, tree, and car have an effect on $PM_{2.5}$ dispersion [68,87,88]. Finally, during the data analysis stage, descriptive statistical analysis was conducted on these 10 key built environment factors using IBM SPSS Statistics 26 software. Table 3 shows the descriptive statistics of the 10 built environment factors.

Table 3. Descriptive statistics of 10 built environment factors.

Number	Elements	Min	Max	Mean	STD
1	Sky	0.000	0.632	0.260	0.136
2	Building	0.000	0.892	0.250	0.173
3	Road	0.000	0.415	0.173	0.077
4	Tree	0.000	0.746	0.127	0.111
5	Car	0.000	0.344	0.045	0.052
6	Sidewalk	0.000	0.379	0.041	0.042
7	Wall	0.000	0.774	0.020	0.046
8	Plant	0.000	0.464	0.018	0.029
9	Fence	0.000	0.351	0.014	0.023
10	Grass	0.000	0.331	0.011	0.023

Note: The built environment factors in the table are sorted in descending order based on the mean value. Data were extracted from 33,466 street-view panoramas in the study area.

The research findings indicate significant differences among the 10 built environment factors in terms of minimum, maximum, mean, and standard deviation values. Sky, as a crucial component of urban landscapes, not only represents the openness of the sky but also affects surface temperature and air quality. In this study, the sky factor exhibited the highest proportion in Street View Imagery, with a mean value of 0.260. However, substantial fluctuations were observed across the study area, with a minimum value of

0.000, a maximum value of 0.632, and a standard deviation of 0.136. These findings suggest significant disparities in the sky factor across different neighborhoods within the study area. Such disparities may be attributed to factors such as neighborhood building density and street orientation.

Buildings, as an important part of the urban built environment, have a density that affects air quality, the urban heat island effect, ventilation conditions, and the comfort of residents. In this study, the building factor demonstrates a mean value of 0.250, which is second only to the sky factor, indicating its dominant presence in the Street View Imagery of the study area. The minimum and maximum values of 0.000 and 0.892 reveal substantial spatial heterogeneity in building distribution, with localized areas exhibiting high-density development patterns. A standard deviation of 0.173 underscores the complexity and diversity of urban building densities across the study area, which may contribute to microclimatic variations.

As an important part of the urban transportation system, the width, density, and traffic flow of roads affect urban traffic conditions, air quality, and accessibility. In this study, the mean value of the road factor is 0.173, which is lower than the sky and building, but still an important part of the urban built environment. The standard deviation is 0.077, which indicates that roads in the study area are characterized by an unbalanced distribution.

Trees, as critical components of the urban green space system, significantly contribute to improving urban air quality and influencing PM_{2.5} dispersion and deposition. In this study, the tree factor exhibits a mean value of 0.127, with a maximum of 0.746, indicating that while street green spaces remain limited, certain areas demonstrate effective tree preservation and utilization, achieving relatively high coverage rates. However, a standard deviation of 0.111 reveals considerable data variability, reflecting the uneven spatial distribution of street green spaces across the study area.

In this study, the minimum value of the car factor is 0.000, the maximum value is 0.344, the mean value is 0.045, and the standard deviation is 0.052. As an important component of urban transportation, the effect of cars on air quality mainly involves two aspects: one is the bluff body effect, which physically obstructs airflow, and the other is their role as a source of PM_{2.5} emissions. However, since Street View Imagery is static, the car factor extracted from it primarily reflects the former—the obstruction effect on airflow—while it cannot effectively distinguish between moving and parked vehicles, nor directly capture emission information.

Sidewalks, as critical components of urban transportation systems, have a significant effect on traffic accessibility through their quantity, density, and width. In this study, the sidewalk factor exhibits a mean value of 0.041, a maximum of 0.379, and a standard deviation of 0.042, indicating significant variations in sidewalk infrastructure across different neighborhoods.

Walls, as boundary elements of urban space, reflect wall facade visibility and spatial closure. In this study, the mean value of the wall is 0.020, and the standard deviation is 0.046. This shows the unevenness of the distribution of the wall factor in the study area. This inhomogeneity may be due to different urban planning and the choice of building materials in different areas.

Plants, as critical components of the urban green space system, have a significant effect on urban air quality and ecological quality through their species composition, quantity, and spatial distribution. In this study, the plant factor exhibits a mean value of 0.018 and a standard deviation of 0.029, indicating limited spatial distribution across the study area.

As an important tool for urban space management, the type, height, and density of fences affect the urban interface, the tidiness and safety of the urban landscape, and the travel behavior of residents. In this study, the mean value of fences is 0.014, which is low

but still has some presence in the Street View Imagery. The maximum value of the fence factor is 0.351, indicating that some neighborhoods are densely fenced, which may be closely related to the needs of urban space management in some areas.

Grass, as a critical component of the urban green space system, has a significant effect on urban microclimates, surface temperatures, and air quality. In this study, the grass factor exhibited a minimum value of 0.000, a maximum value of 0.331, and an average value of 0.011. These results suggest that grass distribution within the study area is relatively sparse and uneven.

In summary, the descriptive statistical analysis of the ten built environment factors systematically reveals their distribution characteristics and data quality, accurately grasps the distribution patterns of the data, and identifies potential anomalies. Through this analysis, it ensures the accuracy and credibility of the research findings and provides a solid foundation for subsequent spatial heterogeneity analysis.

3.2. Spatial Distribution of PM_{2.5} Concentrations

The study obtained PM_{2.5} concentration data from the National Tibetan Plateau Data Center. The annual average PM_{2.5} concentration in the study area ranged from 45.6 $\mu\text{g}/\text{m}^3$ to 52.7 $\mu\text{g}/\text{m}^3$ during 2023. Figure 4a illustrates the spatial distribution of PM_{2.5} concentrations in Xi'an City (China) during 2023.

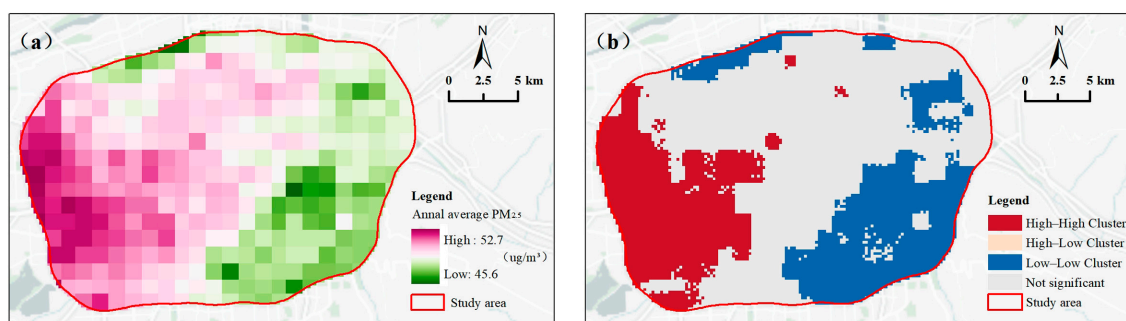


Figure 4. Spatial distribution and local spatial autocorrelation analysis of PM_{2.5} concentrations in Xi'an City, 2023: (a) spatial distribution of PM_{2.5} concentrations; (b) local spatial autocorrelation distribution of PM_{2.5} concentrations.

In this study, spatial autocorrelation analysis of PM_{2.5} concentration was conducted to reveal the characteristics of the spatial distribution of PM_{2.5} concentration in the study area. The results of the global Moran's index and local Moran's index analysis are as follows. The results of the global Moran's index analysis showed that the Moran's I index was 0.97, indicating a positive spatial effect of PM_{2.5} concentration. The p -value was 0.00 (p -value < 0.01), and the z -value was 148.11 (z -value > 2.58). It indicates that the distribution of PM_{2.5} concentration in the study area shows a clustering trend. The results of the localized Moran index analysis showed that high and low values were spatially clustered, with high-high clusters mainly concentrated in the west side of the study area, and low-low clusters mainly concentrated in the southeast and northeast side of the study area. High-low clusters and low-high clusters are relatively rare in the study area. Figure 4b shows the local spatial autocorrelation distribution.

3.3. Spatial Regression Results

(1) OLS model regression results

In this study, the OLS model was first used to initially explore the linear relationships between the 10 variables and PM_{2.5} concentrations in the microscale built environment. In the OLS model, the VIF values of the 10 variables were lower than 3.760, which indicated

that there was no significant multicollinearity problem among the variables selected in this study. The results of this model showed an R^2 of 0.030, an adjusted R^2 of 0.029, and an AICc of 38506.261. In addition, the p -value of the Koenker (BP) statistic was 0.000 (p -value < 0.01), which indicated that the OLS modeling relationship was non-stationary and there was spatial heterogeneity in the variables. Therefore, further in-depth analysis using GWR modeling is necessary.

(2) GWR model regression results

This study was further analyzed using the GWR model, which is able to account for spatial heterogeneity. The results of this model showed an R^2 of 0.916, an adjusted R^2 of 0.908, and an AICc of 11,379.701, which suggests that this model is a better fit than the OLS model. However, the GWR model with the same bandwidth settings for all explanatory variables has some limitations in explaining spatial heterogeneity and needs to be further analyzed using the MGWR model.

(3) MGWR model regression results

MGWR is a further improvement of the GWR model, which allows different bandwidths to be set for different explanatory variables with higher accuracy and more precise refinement of the spatial heterogeneity of the different variables. The results of the MGWR model show an R^2 of 0.981 and an adjusted R^2 of 0.974, indicating a high goodness-of-fit. Compared with the OLS model (AICc = 32,970.558) and the GWR model (AICc = 11,379.701), the MGWR model exhibits a marked decrease in AICc to −3897.948. Meanwhile, the residual standard deviation (Sigma) decreases from 0.385 (GWR) to 0.163 (MGWR). These simultaneous reductions in AICc and Sigma suggest that the improved fit is due to the superior performance of the MGWR model rather than overfitting. The robustness of the model is further supported by its ability to assign distinct bandwidths to each variable, with specific variables operating at different spatial scales, such as Building (bandwidth of 43.000) representing a highly local influence and Grass (bandwidth of 9870.000) representing an essentially global influence.

This study compares the modeling performance of OLS, GWR, and MGWR models, respectively. The results show that the OLS model has the smallest adjusted R^2 value and the largest AICc value. The MGWR model has the largest adjusted R^2 value and the smallest AICc value. This indicates that the MGWR model has the best fit and is better than the GWR and OLS models. The MGWR model can aptly reveal the spatial heterogeneity of the relationship between the microscale built environment and $PM_{2.5}$ concentration. Table 4 shows the comparison of regression results of OLS, GWR, and MGWR models. Figure 5 illustrates the regression coefficient maps of the ten built environment factors derived from the MGWR model.

Table 4. Comparison of regression results for OLS, GWR, and MGWR models.

--	OLS Coefficients		GWR Coefficients			MGWR Coefficients			
Variables	Mean	Mean	Min	Max	Bandwidth	Mean	Min	Max	Bandwidth
Sky	1.250	−0.111	−6.569	3.961	1380.539	0.002	−0.486	0.836	47.000
Building	0.653	0.035	−3.288	2.575	1380.539	0.017	−0.852	3.140	43.000
Road	−1.809	0.320	−5.652	7.057	1380.539	0.000	−0.134	0.169	322.000
Tree	0.268	−0.271	−3.920	2.105	1380.539	0.003	−0.012	0.012	2890.000
Car	−1.225	0.492	−9.216	16.746	1380.539	−0.001	−3.654	1.463	43.000
Sidewalk	−4.313	0.131	−6.915	13.111	1380.539	−0.010	−4.198	0.698	43.000
Wall	−0.144	0.712	−3.829	8.230	1380.539	0.006	−0.029	0.045	1008.000
Plant	1.226	0.098	−25.415	12.417	1380.539	−0.009	−0.028	0.005	2503.000
Fence	−5.835	−0.460	−33.791	15.895	1380.539	0.004	−0.961	0.964	47.000
Grass	−8.254	0.718	−14.533	24.936	1380.539	0.001	−0.002	0.005	9870.000
R^2	0.030			0.916				0.981	
Adj. R^2	0.029			0.908				0.974	
AICc	38,506.261			11,379.701				−3897.948	

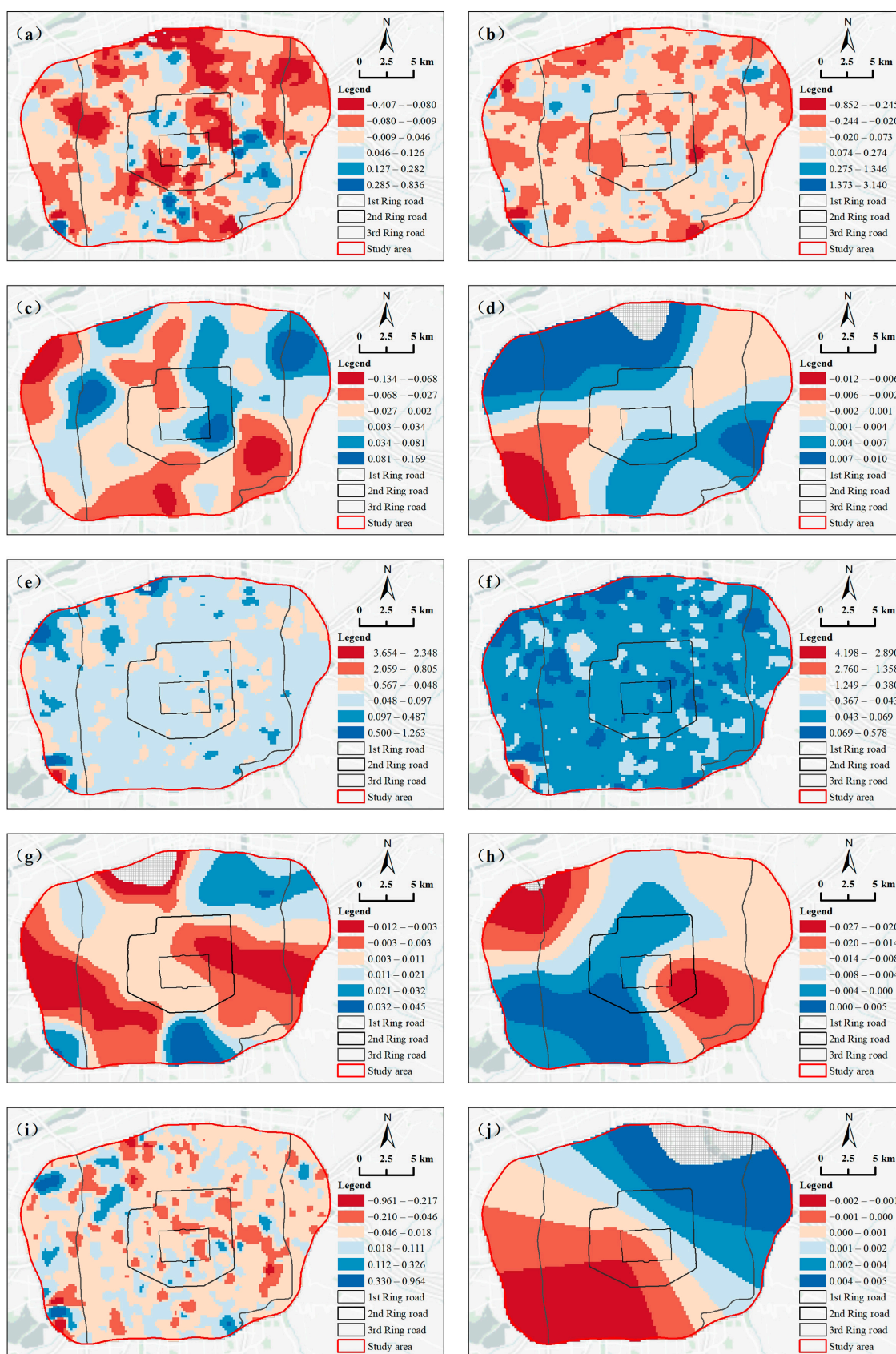


Figure 5. MGWR regression coefficient map for 10 built environment factors in Xi'an: (a) Sky; (b) Building; (c) Road; (d) Tree; (e) Car; (f) Sidewalk; (g) Wall; (h) Plant; (i) Fence; (j) Grass.

The MGWR model revealed the effects of 10 built environment factors on $PM_{2.5}$ concentrations, and there was significant spatial heterogeneity in these effects. The specific analysis of the regression coefficients of the MGWR model is presented below:

Firstly, Table 4 presents the optimal bandwidths for different factors within the MGWR model. By assigning factor-specific optimal bandwidths, the MGWR model optimizes its fitting performance. The results reveal substantial variations in bandwidths across these factors. Notably, factors such as road, tree, wall, plant, and grass exhibit relatively large bandwidths, spanning from 322.000 to 9870.000. This suggests that the effect of these variables on $PM_{2.5}$ concentrations manifests at broader spatial scales, with regression coefficients exhibiting weaker spatial heterogeneity. Conversely, factors including sky, building, car, sidewalk, and fence demonstrate relatively small bandwidths, ranging between 43.000 and 47.000. This indicates a localized effect of these factors on $PM_{2.5}$ concentrations, accompanied by stronger spatial heterogeneity in their regression coefficients.

Furthermore, Table 4 presents the mean, minimum, and maximum values of regression coefficients for each factor within the MGWR model. A detailed analysis of each factor's regression coefficients is provided as follows:

The sky factor represents the degree of openness of the sky. Its average coefficient is positive (average coefficient of 0.002), which indicates that the sky factor has a positive effect on $PM_{2.5}$ concentration. It reflects that the lack of vegetation cover in the open sky area causes $PM_{2.5}$ dispersion to be affected. The sky factor demonstrates a maximum coefficient of 0.836 and a minimum of -0.486 , indicating regional variations in its effect across different areas.

The building factor demonstrates a positive effect on $PM_{2.5}$ concentrations (average coefficient of 0.017). This suggests that densely built environments may impede airflow, thereby obstructing $PM_{2.5}$ dispersion. The building factor exhibits a maximum coefficient of 3.140 and a minimum of -0.852 , indicating spatial disparities in its effect across localized regions.

The average coefficient of the road factor is 0.000, with a minimum value of -0.134 and a maximum value of 0.169, which indicates that the road factor as a whole has a weak effect on the $PM_{2.5}$ concentration, but there are some differences in localized areas.

The average coefficient of the tree factor is positive (0.003, with minimum and maximum values of -0.012 and 0.012, respectively). This may be related to the limitations of Street View Imagery, which mainly captures horizontal perspectives of the built environment and may have limited ability to reflect differences in tree species or the vertical structure of tree canopies.

The average coefficient of the car factor is negative (-0.001), with minimum and maximum values of -3.654 and 1.463, respectively. This may reflect the effects of other factors on the car factor. Street View Imagery performs well in extracting static features of the built environment; therefore, the extracted car factor primarily reflects static characteristics, but it has limitations in capturing dynamic features, such as traffic flow or vehicle density.

The average coefficient of the sidewalk factor is negative (average coefficient of -0.010), with minimum and maximum values of -4.198 and 0.698, respectively. This suggests that the sidewalk factor has a negative effect on $PM_{2.5}$ concentrations. Sidewalk width and pedestrian friendliness enhancement may reduce short-distance motor vehicle use, and locally isolated sidewalks with greenery may reduce $PM_{2.5}$ concentrations.

The mean coefficient of the wall factor is positive (mean coefficient of 0.006), which indicates that the wall factor positively affects the $PM_{2.5}$ concentration. The minimum and maximum values of the wall factor were -0.029 and 0.045, respectively. This indicates that the effect between the two varies considerably in the study area, with localized continuous walls impeding ventilation and exacerbating pollutant accumulation.

The average coefficient of the plant factor was negative (mean coefficient of -0.009), which indicated that the plant factor had a negative effect on the $PM_{2.5}$ concentration, and three-dimensional greening plants would significantly inhibit $PM_{2.5}$, and the plant dust retention efficiency was affected by the hierarchical structure of the vegetation and the maintenance status. The minimum and maximum values of the plant factor were -0.028 and 0.005 , respectively, which indicated that there were differences in the effects of the plant factor on $PM_{2.5}$ concentration.

The fence factor demonstrates a positive mean coefficient (mean coefficient of 0.004), with coefficient values ranging from -0.961 to 0.964 . This indicates that fences exert a positive effect on $PM_{2.5}$ concentrations within the study area. Functioning as physical barriers, permeable fences enhance ventilation while solid fences exacerbate pollution accumulation.

The average coefficient of the grass factor was 0.001 , with a minimum value of -0.002 and a maximum value of 0.005 , which indicates that the grass factor has a weak effect on $PM_{2.5}$ concentrations, but there is some variation in localized areas.

In conclusion, the results of the MGWR model showed that the 10 built environment factors in the study area had significant effects on the spatial heterogeneity of $PM_{2.5}$ concentrations. Based on the positive and negative regression coefficients and the strength of their effects, they can be categorized into the following three categories. The first category—buildings, walls, and fences—has a strong positive effect on $PM_{2.5}$, and the strength of their effect may be related to pollutant retention in high-density built environments. Trees, sky, and grass have a weak positive effect on $PM_{2.5}$ concentrations, which may be associated with vegetation blocking diffusion or open space inversion effects. This may also be related to the limitation of Street View Imagery, which mainly captures horizontal perspectives and may not fully reflect differences in tree species, vegetation types, or canopy structures. The second category—sidewalks, plants, and cars—has certain negative regression effects on $PM_{2.5}$ concentrations. On one hand, this reflects the potential of pedestrian-friendly design, vegetation adsorption, and traffic management to mitigate $PM_{2.5}$ pollution. On the other hand, car factors extracted from Street View Imagery mainly capture static characteristics and are limited in representing dynamic features, such as traffic flow or vehicle density, which may affect the regression results. The third category—compared with other built environment factors, the overall effect of the road factor on $PM_{2.5}$ concentrations is relatively weak.

This study employed the MGWR model to investigate the spatial heterogeneity relationship between built environment factors and $PM_{2.5}$ concentrations. The following presents a detailed analysis of the spatial distribution patterns of these regression coefficients:

The sky factor exhibits an overall positive effect on $PM_{2.5}$ concentrations, yet with pronounced spatial heterogeneity. Areas demonstrating a significantly positive effect are primarily concentrated in the industrial heritage zone outside the Second Ring Road, specifically the old industrial bases surrounding the Xingfu Forest Belt, where dense factory clusters impede pollutant diffusion. Additionally, the urban–rural transition zone southwest of the Ring Expressway is also positively significant, likely due to village sprawl and fragmented open spaces in this region. Conversely, areas with significant negative effects are predominantly located in large parks and green spaces, such as Daming Palace National Heritage Park and Xingqing Palace Park within the Second Ring Road, and in science and education clusters. They are also found near numerous parks, including Xi'an World Horticultural Expo Park and Qujiang Lake Heritage Park, both inside and outside the Third Ring Road.

The building factor has a positive effect on the $PM_{2.5}$ concentration as a whole, but with significant spatial heterogeneity. The significant positive effect areas are mainly concen-

trated in the high-density built-up area of the city. They are distributed in the northwestern part of the Second Ring Road and in the densely built-up area from the Second Ring Road to the southeastern part of the Third Ring Road, peaking around the villages in the southwestern part of the Ring Expressway due to the agglomeration of low-rise contiguous building clusters. Significant negative effect areas are mainly concentrated around Changle Park in the eastern part of the Second Ring Road, parks along the Third Ring Road, and near a number of industrial parks in the western part of the Ring Expressway.

The road factor exhibits a relatively weak overall effect on $PM_{2.5}$ concentrations but demonstrates localized positive and negative effects. Notable positive effect zones primarily concentrate in the southeastern sections of the First and Second Ring Roads, as well as along the eastern and western stretches of the Third Ring Road. Conversely, significant negative effect areas are mainly distributed in the southern part of the Third Ring Road. Multiple urban parks, including Yongyang Park, Tang City Wall Ruins Park, Qujiang Lake Heritage Park, and Xi'an Botanical Garden, are located there, contributing to $PM_{2.5}$ mitigation. Additionally, negative effects are observed near the Dongfang Factory on the eastern Third Ring Road and industrial parks northwest of the Ring Expressway.

The tree factor generally exhibits a positive effect on $PM_{2.5}$ concentrations; however, spatial variations exist within the study area. Limited tree distribution and low green coverage in urban centers contribute to their limited effectiveness in reducing $PM_{2.5}$ concentrations. In contrast, areas southwest and northeast of the Ring Expressway, adjacent to regions such as Kunmingchi Qixi Park and Xi'an World Horticultural Expo Park, demonstrate a significant negative effect on $PM_{2.5}$ concentrations.

The car factor has a weak negative effect on the $PM_{2.5}$ concentration as a whole, but there is significant spatial heterogeneity. The significant positive effect area is mainly concentrated in the north side of the Third Ring Road and the northwestern part of the city ring road, and around the city highway near the industrial park. The significant negative effect area is mainly concentrated along the city ring road and the Ring Expressway.

The sidewalk factor had an overall negative effect on $PM_{2.5}$ concentrations, but there was significant spatial heterogeneity. Except for the urban ring road and along the Ring Expressway in the study area, the sidewalk factor showed a significant negative effect on $PM_{2.5}$ concentration in most parts of the study area.

The wall factor exhibits an overall positive effect on $PM_{2.5}$ concentrations. Except for the southwestern and southeastern regions of the study area, dense building facade areas demonstrate a significant positive effect on $PM_{2.5}$ concentrations across most regions.

Except for the urban–rural transition zone in the southwestern zone of the study area, most of the areas of the study area showed significant negative effects of plant factors on $PM_{2.5}$ concentrations. Among them, a significant negative effect was presented near several areas with better ecological environments, such as Changle Park, Xingqing Park, and Qinglong Temple Heritage Park.

The fence factor has an overall positive effect on $PM_{2.5}$ concentrations, but there is significant spatial heterogeneity. The area of significant positive effect is mainly concentrated in the vicinity of industrial parks in the western part of the Ring Expressway. The zone of significant negative effect is mainly concentrated in the north of the Third Ring Road and the southeast near the Oriental Factory.

The grass factor had an overall positive effect on $PM_{2.5}$ concentrations. However, there were some differences in the study area. The area of significant positive effect is mainly concentrated in the northeast of the study area. However, in the southwest of the study area, the grass factor in Yongyang Park, Tang City Wall Heritage Park, and Fengqing Park had a significant negative effect on $PM_{2.5}$ concentrations.

In summary, the distribution characteristics of regression coefficients for the ten built environment factors in the study area indicate significant differences in their effect intensity and spatial distribution on PM_{2.5} concentrations. This finding not only reveals the complex nonlinear relationships between these ten built environment factors and PM_{2.5} concentrations but also challenges the conventional homogeneous governance model under the “one city, one policy” framework. Consequently, subsequent strategies should be formulated with precise optimization measures based on spatial heterogeneity characteristics.

4. Discussion

4.1. Effects of Micro-Scale Built Environment on PM_{2.5} Pollution

In this study, semantic segmentation of Street View Imagery was employed to quantify the morphological characteristics of the urban built environment, enabling the extraction of key indicator variables influencing PM_{2.5} concentration distributions. Three regression models, OLS, GWR, and MGWR, were comparatively analyzed, and the MGWR model was selected as optimal for this study. The relationship between the urban built environment and PM_{2.5} pollution was analyzed using MGWR, revealing the effect of significant spatial heterogeneity.

Firstly, the study findings indicate that buildings and walls exert a significant positive effect on PM_{2.5} concentrations. At the microscale, the layout of buildings and walls can impede PM_{2.5} diffusion by reducing air ventilation efficiency, which aligns with the research results of Wu et al. [89]. Generally, urban greening plays a certain mitigating role in PM_{2.5} concentrations. However, this study discovered a positive effect between trees, grass, and PM_{2.5} concentrations in localized areas of the study region. This finding has also been confirmed in relevant studies, indicating that the effect of urban vegetation on air quality is more complex than previously assumed. Trees and other vegetation may hinder ventilation and reduce air circulation, thereby affecting pollutant dispersion [90]. Urban greening at the street level may exacerbate air pollution [91]. The study results demonstrate that unreasonable sky view factors in densely built-up industrial areas and areas near the rural–urban fringe can impede air circulation and aggravate air pollution. This is consistent with the research findings of Fan et al., who pointed out a significant effect between sky view factors and PM_{2.5} concentrations [92].

Secondly, the mitigating effect of urban parks on air pollution has been widely confirmed. This study further corroborates this conclusion, revealing a significant negative effect between plant factors near numerous parks within the study area and PM_{2.5} concentrations. This finding is consistent with previous research, such as that conducted by Li et al., which demonstrated that increased vegetation coverage around urban parks significantly expands the PM_{2.5} reduction range [93]. Notably, the car factor exhibits a weak negative correlation with PM_{2.5} concentrations. This phenomenon can be attributed to several factors. On one hand, the city of Xi'an has witnessed a continuous increase in the number of clean energy vehicles in recent years, effectively reducing the intensity of vehicle exhaust emissions. On the other hand, the study area is situated within the Xi'an Ring Expressway, characterized by a high level of urbanization and well-developed infrastructure, including comprehensive charging facilities that facilitate the widespread adoption of clean energy vehicles. Relevant studies also indicate that the transition to electric vehicles can significantly reduce PM_{2.5} concentrations and improve urban air quality [94]. Moreover, the car factor in this study was extracted from Baidu Street View Imagery. Street View Imagery can be used to detect the number and types of vehicles on the road, but it mainly records static features. Due to this characteristic, Street View Imagery has difficulty distinguishing moving vehicles from parked ones and cannot track vehicle movement or real-time emission data. This limitation has also been confirmed in studies by Biljecki et al. [39].

Furthermore, the road factor exhibits a relatively weak overall effect on PM_{2.5} concentrations. However, it demonstrates a significant positive effect along the southeastern and eastern-western sections of the urban ring road. This phenomenon may be attributed to the ring road serving as a major urban artery, carrying substantial traffic volume, which leads to elevated PM_{2.5} concentrations. This finding aligns with the research conducted by Wang et al., who observed a notable increase in PM_{2.5} concentrations in areas with dense high-grade road networks, such as along ring roads [95]. Additionally, this study reveals a significant negative effect of the road factor on PM_{2.5} concentrations in park-dense areas, which is consistent with the research findings of Du et al. [96].

4.2. Optimization Strategies

With the gradual transformation of urban construction in China toward high-quality development, PM_{2.5} pollution mitigation has become a core issue in ecological environment governance. In response to the urgent need for air pollution prevention and control, the state has successively issued systemic policy documents to improve air quality. Notably, the 2025 Implementation Plan for Beautiful City Construction further focuses on key areas and prominent issues of the urban ecological environment, explicitly mandating the enhancement of urban ecological quality. As one of the first batch of pilot cities for urban renewal in China (designated in 2021) and the sole pilot city in Shaanxi Province, Xi'an confronts the dual imperative of reconciling PM_{2.5} pollution mitigation with the optimization of its built environment during its ongoing new urbanization process.

In the face of various problems in urban development, urban renewal has become an important research topic of common concern for domestic and international academics [97]. Its core lies in the comprehensive optimization of urban economy, culture, environment, and other dimensions [98]. In this context, urban street space, as an important part of urban public space, is also the main place for residents' daily activities, and its environmental quality is directly related to the health and well-being of residents. Therefore, it is particularly important to conduct a refined quantitative analysis of urban environmental characteristics [99]. This can not only provide a scientific basis and data support for urban renewal and air pollution control but also provide decision support for optimizing urban spatial layout, improving air quality, and upgrading ecological environment quality.

Based on the bandwidths, regression coefficients, and spatial distribution characteristics of various factors revealed by the MGWR model, this study proposes the following optimization strategies. Firstly, regarding the differences in bandwidth among factors, it is recommended that local governments emphasize not only macroscale regional collaborative governance but also microscale interventions. The importance of tailoring strategies to local conditions should be highlighted, implementing differentiated governance measures to accommodate the complex spatial heterogeneity within cities.

Secondly, for factors such as buildings, walls, and fences, it is suggested to pay attention to optimizing the openness of urban spatial interfaces during urban renewal. In areas with dense buildings, it is suggested to reasonably manage building spacing to maintain ventilation. In areas with dense industrial buildings and along the Ring Expressway, it is suggested to optimize land-use layout and the configuration of open spaces. The addition of vertical green walls on building facades is also suggested to enhance ecological performance. For fences with high enclosures, promoting green-permeable fences is suggested to reduce facade closure, with particular attention to improving areas around the western industrial park along the Ring Expressway. Additionally, it is suggested to optimize the urban green structure to avoid excessive planting that may hinder pollutant dispersion.

Finally, for factors such as sidewalks, plants, and cars, it is suggested to focus on improving the pedestrian environment along urban ring roads and the Ring Expressway,

enhancing sidewalk continuity. It is suggested to optimize the layout of the urban green space system to increase plants' capacity for pollutant absorption. It is also suggested to promote low-emission or cleaner vehicles, implement a public-transport-first strategy, and strengthen the management of motor vehicle emissions. At the same time, it is suggested to reinforce the road pollution monitoring network on urban ring roads and main roads to achieve refined pollution management.

In conclusion, most of the existing air pollution control strategies follow the macro governance framework of "one city, one policy". Although certain achievements have been made at the regional scale, they tend to overlook the micro differences in the built environment elements within cities. This study has promoted the transformation of thinking in PM_{2.5} pollution control from "homogeneous control" to "differentiated control", systematically revealing the influence of factors such as the sky, building, and plant on the spatial heterogeneity of PM_{2.5} concentration. This not only provides a scientific basis for avoiding the "one-size-fits-all" policy in environmental protection but also provides an optimization basis for the layout of buildings and green space systems in urban planning. It is also a response to the strategy of "precise pollution control, scientific pollution control, and law-based pollution control" in the "Action Plan for Continuous Improvement of Air Quality" issued by The State Council in 2023. Although this study focuses on Xi'an, the multidisciplinary research framework established here can be extended to other similar cities.

4.3. Research Limitations and Future Directions

This study primarily adopts a method combining Street View Imagery and machine learning to quantify the microscale built environment. Investigating the spatial heterogeneity effects of microscale built environments on PM_{2.5} concentrations demonstrates a certain degree of innovation. However, this study still has the following limitations:

(1) Geographical Limitations: This study analyzes data from one city in one year. Differences in built environments across countries, cities, or years are not considered. Google Street View data are not available for Xi'an; therefore, Baidu Street View is used. This may limit cross-platform comparisons and the generalizability of the findings. Future research suggestions should validate the results in regions with multiple street view platforms.

(2) Update Frequency Limitations: This study uses commercial Street View platforms, whose irregular update frequency limits their applicability for continuous temporal analyses. To address this limitation, future studies could consider using continuous time-series or multi-year Street View Imagery, for example, by supplementing commercial data with self-collected images, to further investigate the dynamic variations of PM_{2.5} concentrations.

(3) Multifactorial Integration Limitations: This study primarily relies on Street View Imagery, which captures only street-level visuals and does not account for data such as rooftop emissions or indoor sources. Future research should integrate multi-source datasets, particularly topography, meteorological, socio-economic, and other emission-related data, to construct a more comprehensive analytical model. This approach can enhance the robustness, accuracy, and comprehensiveness of the research findings and better capture the full range of determinants influencing PM_{2.5} concentrations.

(4) Limitations of Semantic Segmentation and Feature Extraction: This study applies semantic segmentation to Street View Imagery using the ResNet50 deep learning model and the ADE20K dataset, and the overall model performance is robust. However, this approach still has certain limitations in capturing dynamic characteristics and fine-grained features. For example, when quantifying the car factor, Street View Imagery finds it difficult to distinguish between parked and moving vehicles, which limits the accurate reflection of real-time vehicle emissions. When extracting vegetation factors, horizontal viewing

angles limit the identification of canopy structures and vegetation types. Future research should address these limitations by integrating multi-source data, improving semantic segmentation algorithms, and enhancing the accuracy of feature recognition.

5. Conclusions

This study integrates multidisciplinary knowledge from urban planning, environmental science, computer science, and geographic information science (GIS) to overcome the limitations of a single disciplinary perspective and to form an integrated environment–technology–planning analysis paradigm for interdisciplinary research on PM_{2.5} concentrations. By combining Street View Imagery with machine learning techniques, it addresses the limitations of traditional two-dimensional data at the microscale, enabling the quantification of urban built environments from three-dimensional and microscale perspectives. A research framework titled “Street View Imagery Element Extraction—Spatial Heterogeneity Modeling—Planning Strategy Optimization” was constructed, uncovering the spatially heterogeneous relationships between microscale built environments and PM_{2.5} concentrations and demonstrating a certain degree of innovation. The key findings are summarized as follows:

(1) Ten microscale built environment factors in the study area exhibit spatially heterogeneous effects on PM_{2.5} concentrations.

(2) This study compares OLS, GWR, and MGWR spatial regression models. The results indicate that the MGWR model has the highest goodness-of-fit, accurately explaining the spatially heterogeneous effects of microscale built environment factors on PM_{2.5} concentrations.

(3) Significant differences exist in the spatially heterogeneous effects of the ten microscale built environment factors on PM_{2.5} concentrations. Among them, positive effect factors ranked by strength are building, wall, fence, tree, sky, and grass; negative effect factors ranked by strength are sidewalk, plant, and car. In contrast, road factors have a relatively weaker overall effect on PM_{2.5} concentrations.

This study systematically reveals the spatially heterogeneous effects of the microscale built environment on PM_{2.5} concentrations through a multidisciplinary cross-cutting approach, which may provide new insights for PM_{2.5} pollution management. The research results are conducive to formulating effective air pollution policies, optimizing urban planning, design, and management, and have certain reference significance for promoting ecological civilization construction, facilitating sustainable development, building healthy cities, and achieving United Nations Sustainable Development Goals 3.9 and 11.6.2.

Author Contributions: T.H. was involved in the overall conception and design of the study and led the drafting and finalization of the manuscript. K.W. participated in the formulation of the research plan, data collection, and analysis, and contributed to the initial draft of the manuscript. Y.W. made substantial intellectual revisions to the content. L.W. contributed to the review and revision of the manuscript, provided key suggestions, and jointly finalized the approved version. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the ‘Scientists + engineers’ team development project of YuLin High Tech Industrial Development Zone under Grant YGXKG-2023-105 and the National Key R & D Program under Grant 2022YFE0119200.

Data Availability Statement: Data will be provided upon request. Any questions should be addressed to the corresponding author.

Acknowledgments: The authors thank the National Tibetan Plateau Data Center for providing the High-resolution and High-quality Ground-level PM_{2.5} Dataset for China.

Conflicts of Interest: The authors report there are no competing interests to declare.

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